IDENTIFYING CUSTOMER INTEREST FROM SURVEILLANCE CAMERA BASED ON DEEP LEARNING

A Mini Project Report

submitted by

ANJALI TP (MES20MCA-2008)

to

the APJ Abdul Kalam Technological University
in partial fulfillment of the requirements for the award of the Degree

of

Master of Computer Applications

Department of Computer Applications

MES College of Engineering
Kuttippuram, Malappuram - 679 582

February 2022

DECLARATION

I undersigned hereby declare that the project report **IDENTIFYING CUSTOMER INTEREST FROM SURVEILLANCE CAMERA BASED ON DEEP LEARNING**, submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala, is a bona fide work done by me under supervision of Prof:Mr.Balachandran KP, Assistant Professor, Department of Computer Applications. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

Place:Kuttipuram

....

Date:28/02/2022

DEPARTMENT OF COMPUTER APPLICATIONS
MES COLLEGE OF ENGINEERING, KUTTIPPURAM

CERTIFICATE

This is to certify that the report entitled **IDENTIFYING CUSTOMER INTEREST FROM SURVEILLANCE CAMERA BASED ON DEEP LEARNING** is a bona fide record of the Mini Project work carried out by **ANJALI TP (MES20MCA-2008)** submitted to the APJ Abdul Kalam Technological University, in partial fulfillment of the requirements for the award of the Master of Computer Applications, under my guidance and supervision. This report in any form has not been submitted to any other University or Institution for any purpose.

Internal Supervisor(s) External Supervisor(s)

Head Of The Department

Acknowledgements

At the very outset I would like to thank the Almighty's mercy towards me over the years. I wish to express my sincere thanks to my project guide Mr.Balachandran K.P Associate Professor, Dept. of Master of Computer Applications who guided me for the successful completion of this project. I also thank him for valuable suggestions, guidance, constant encouragement, boundless corporation, constructive comments and motivation extended to me for completion of this project work. I take this opportunity to express my profound gratitude to Ms.Priya J D as my project coordinate her valuable support, timely advise and strict schedules to complete my project I would like to express my sincere thanks to all the staff members of Master of Computer Applications department for their support and valuable suggestion for doing the project work. Last but not least my graceful thanks to my parents, friends and also the persons who supported me directly and indirectly during the project

ANJALI TP (MES20MCA-2008)

Abstract

This project proposes a method to identify a customer's interest in the product. Specifically, I applied the state-of-the-art deep learning algorithms to the real-world surveillance videos for analyzing customer interest in the product and evaluated the accuracy. For this, I first introduce a new first of its kind dataset called ICI (items of customer's interest) that includes various shopping situations. I experimented the state-of-the-art deep learning algorithms on the ICI dataset to determine a suitable algorithm for identifying a customer's interest. The experimental results demonstrated that the estimation accuracy is 71 percentage on the average, meaning that a customer's interest can be measured effectively.

Keywords:Customer interest, Application of AI, Surveillance camera

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background

The main purpose of this project is to identify the customer interest on a product.Identifying customer's interests is valuable as it intuitively represents the product the customer wants.It can also be an effective marketing strategy for determining potential customers.identifying a customer's interest based on behaviors from surveillance cameras. I detect the customer's gaze direction as this behavior accurately reflects customer interest in a particular product.An item of customer interest (ICI) dataset that contains various customer behaviors, such as stopping before a product and gazing at a product. I experimented the state-of-the-art deep learning algorithms on the ICI dataset to determine a suitable algorithm for identifying customer interest. The experimental results demonstrate that OpenPose based gaze direction algorithm is efficient in identifying customer interest.

1.1.1 Motivation

Identifying customer's interests is valuable as it intuitively represents the product the customer wants. It can also be an effective marketing strategy for determining potential customers. Therefore, large retail vendors like Walmart and Costco analyze customer purchase history to identify customer interest. However, purchase history alone cannot fully determine how much interest in the product a customer has other than what they have purchased. In other words, products that the customer does not purchase but are interested can never be identified.

1.2 Objective

identify customer interest, it is necessary to analyze customer behaviors in a real-life shopping situation. In a real-life store, there is a shopping situation as well as general situations like walking, looking around something, and talking to each other. However, to effectively analyze customer behaviors while shopping, we need situations that represent customer and product. For this, we collected surveillance videos that contain various customer behaviors, such as stopping in front of a product and gazing at a product. The videos are obtained via YouTube, where we use different languages during the search to maximize the variety and number of videos. The dataset consists of the videos captured by real-world CCTV surveillance cameras, with various angles, different lighting conditions, and different resolution quality. This paper proposes a method to identify customer's interests in the product through the estimation of gaze direction. For effective identification, the FER dataset with various quality and conditions, including various behaviors of customers in the real-world store, was proposed. Considering that the accuracy of gaze direction depends on face detection, I applied the state-of-the-art face detection algorithms to the FER dataset

1.3 Report Organization

The project report is divided into four sections. Section 2 describes literature survey. Section 3 describes the methodology used for implementing the project. Section 4 gives the results and discussions. Finally Section 5 gives the conclusion.

Chapter 2

Literature Survey

Demonstrate the customer's interest classification accuracy. the results of applying face detection methods, which are essential for estimation of gaze direction, to the ICI dataset and measuring the accuracy of them. the accuracy results of the face detection algorithm in various cases. Here, Case 1 represents when the only front side of the customer's face is detected. Case 2 shows the accuracy result when front and right and left sides of the face are detected. Lastly, Case 3 is when face direction swings into all sides. The result of the algorithms demonstrates that MTCNN is heavily influenced by the resolution of the video. Considering that real-life shopping surveillance videos are of low quality, with MTCNN, the accuracy of gaze direction suffers significantly. RetinaFace outperforms MTCNN in all cases. However, the pre-trained model used in RetinaFace contains only faces from -99 degrees to 99 degrees, meaning that faces for other angles are not recognized. OpenPose does not use the pre-trained models. However, it outperforms MTCNN and RetinaFace and outputs 71.3percent. OpenPose demonstrates superior performance compared with MTCNN and RetinaFace because it can detect face direction in all sides even when looking backward or faces that are hard to recognize.demonstrates the results of face detection and estimation of gaze direction using various methods. the results in the situation when the right and left sides of the face are detected. the results when the backsides of the face are detected. MTCNN and RetinaFace except OpenPose cannot detect the backside of the face

Chapter 3

Methodology

3.1 Introduction

Identifying customer's interests is valuable as it intuitively represents the product the customer wants. It can also be an effective marketing strategy for determining potential customers. Therefore, large retail vendors like Walmart and Costco analyze customer purchase history to identify customer interest. However, purchase history alone cannot fully determine how much interest in the product a customer has other than what they have purchased. In other words, products that the customer does not purchase but are interested can never be identified. This paper focuses on identifying a customer's interest based on behaviors from surveillance cameras. I detect the customer's gaze direction as this behavior accurately reflects customer interest in a particular product. More specifically, we make the following contributions: x An item of customer interest (ICI) dataset that contains various customer behaviors, such as stopping before a product and gazing at a product. x,I experimented the state-of-the-art deep learning algorithms on the ICI dataset to determine a suitable algorithm for identifying customer interest. The experimental results demonstrate that OpenPose based gaze direction algorithm is efficient in identifying customer interest

3.2 Modules

Module 1: Admin:

Add and manage Staffs

Add and manage camera

Send Notification to Staff

View Notification

Assign work to staff

View work status

Module 2: Staff:

Login

View works and update status

View notification from admin

View notification from camera

3.3 Developing Environment

Languages used : Python

Front End : HTML, CSS, JAVASCRIPT

Backend : MySQL

Data set : Facial emotion recognition (FER) data set from Kaggle website is used

OS : Windows 7 or Above, Android

Platform used : JetBrains, PyCharm, Android Studio

Frame work : Flask

Technology :Python, Java

Algorithm : Haar Cascade Algorithm, CNN algorithm

3.4 Workflow

I detect the customer's gaze direction as a method to identify customer interest. The process of identifying customer's interests contains three steps: input video, detect a face, and estimate gaze direction. I use the FCE dataset proposed in this Project as an input video. It is essential to accurately detect a face as it influences the accuracy of gaze direction. The face detection and processing are done using deep learning. The collected FER data sets containing CCTV camera footages processed to find the emotions of the customers.

HAAR CASCADE ALGORITHM

The Viola-Jones object detection framework is a machine learning approach for object detection, proposed by Paul Viola and Micheal Jones in 2001. This framework can be trained to detect almost any object, but this primarily solves the problem of face detection in real-time. This algorithm has four steps.

1. Haar Feature Selection

Objects are classified on very simple features as a feature to encode ad-hoc domain knowledge and operate much faster than pixel system. The feature is similar to haar filters, hence the name 'Haar'. An example of these features is a 2-rectangle feature, defined as the difference of the sum of pixels of area inside the rectangle, which can be any position and scale within the original image. 3-rectangle and 4-rectangle features are also used here.

2.Integral Image Representation

The Value of any point in an Integral Image, is the sum of all the pixels above and left of that point. An Integral Image can be calculated efficiently in one pass over the image.

3.Adaboost Training

For a window of 24x24 pixels, there can be about 162,336 possible features that would be very expensive to evaluate. Hence AdaBoost algorithm is used to train the classifier with only the best features.

4.Cascade Classifier Architecture

A cascade classifier refers to the concatenation of several classifiers arranged in successive order. It makes large numbers of small decisions as to whether its the object or not. The structure of the cascade classifier is of a degenerate decision tree.

3.5 USER STORY

A key component of agile software development is putting people first, and user-stories put actual end users at the center of the conversation. Stories use non-technical language to provide context for the development team and their efforts. After reading a user story, the team knows why they are building what they're building and what value it creates. A user story is a tool used in agile software development to capture a description of a software feature from an enduser perspective. The user story describes the type of user, what they want and why. A user story helps to create a simplified description of a requirement. User stories are one of the core components of an agile program. They help provide a user-focused framework for daily work which drives collaboration, creativity, and a better product overall.

User Story ID	As a type of user	I want to <Perform Some Task>	So that I can <Achieve Some Goal>
1	Admin	login	login successful with correct username and password
2	Admin	Add and manage staff	Add ,view,edit,delete the staffs
3	Admin	Add and manage camera	Add ,edit ,delete the camera number
4	Admin	Send notification to staff	Send notification to the staff
5	Admin	View notification	View the notification from camera
6	Admin	Assign work to staff	Assigned work to individual staff
7	Admin	View work status	View the work status
8	staff	login	login successful with correct username and password
9	Staff	View work and update	View the work details and update
10	Staff	View notification from admin	View the notification from admin
11	Staff	View notification from camera	Camera notification is viewed

Figure 3.1: userstory

3.6 PRODUCT BACKLOG

A product backlog is a list of the new features, changes to existing features, bug fixes, infrastructure changes or other activities that a team may deliver in order to achieve a specific outcome.The product backlog is the single authoritative source for things that a team works on. That means that nothing gets done that isn't on the product backlog. Conversely, the presence of a product backlog item on a product backlog does not guarantee that it will be delivered. It represents an option the team has for delivering a specific outcome rather than a commitment.It should be cheap and fast to add a product backlog item to the product backlog, and it should be equally as easy to remove a product backlog item that does not result in direct progress to achieving the desired outcome or enable progress toward the outcome. The Scrum Product Backlog is simply a list of all things that needs to be done within the project. It replaces the traditional requirements specification artifacts. These items can have a technical nature or can be user-centric e.g. in the form of user stories.

User Story ID	Priority <High/Medium/Low>	Size (Hours)	Sprint <#>	Status <Planned/In progress/Completed>	Release Date	Release Goal
1	Medium	2	1	Completed	8-1-2022	Table design
2	High	3		Completed	8-1-2022	Form design
3	High	5		Completed	8-1-2022	Basic coding
4	High	5	2	Completed	22-1-2022	Data set creation
5	Medium	5		Completed	22-1-2022	Detection of face
6	High	5	3	Completed	5-02-2022	customer's gaze direction method
7	Medium	5		Completed	17-2-2022	identify customer interest
8	Medium	5	4	Completed	20-2-2022	Testing data
9	High	5		Completed	20-2-2022	Output generation

Figure 3.2: product backlog

3.7 PROJECT PLAN

A project plan that has a series of tasks laid out for the entire project, listing task durations, responsibility assignments, and dependencies. Plans are developed in this manner based on the assumption that the Project Manager, hopefully along with the team, can predict up front everything that will need to happen in the project, how long it will take, and who will be able to do it.

User Story ID	Task Name	Start Date	End Date	Days	Status
1	Sprint 1	26/12/2021	28/12/2021	2	completed
2		29/12/2021	31/12/2021	3	completed
3		03/12/2021	08/01/2022	5	completed
4	Sprint 2	09/01/2022	16/01/2022	8	Planned
5		18/01/2022	22/01/2022	5	Planned
6	Sprint 3	23/01/2022	27/01/2022	5	Planned
7		30/01/2022	05/02/2022	7	Planned
8	Sprint 4	06/02/2022	10/02/2022	5	Planned
9		16/02/2022	20/02/2022	4	Planned

Figure 3.3: project plan

3.8 SPRINT BACKLOG PLAN

The sprint backlog is a list of tasks identified by the Scrum team to be completed during the Scrum sprint. During the sprint planning meeting, the team selects some number of product backlog items, usually in the form of user stories, and identifies the tasks necessary to complete each user story. Most teams also estimate how many hours each task will take someone to complete.

Backlog item	Status and completion date	Original estimate in hours	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14
User story#1,#2,#3			hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs
Table design	28/12/2021	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Form design	31/12/2021	3	0		1	1	1	0	0	0	0	0	0	0	0	0
Basic coding	08/01/2022	5	0	0	0	0	0	1	1	1	1	1	0	0	0	0
User story #4,#5																
Data set creation	16/01/2022	5	1	1	0	1	1	1	0	0	0	0	0	0	0	0
Detection of face	22/01/2022	5	0	0	0	0	0	0	0	1	1	0	1	1	1	0
User story #6,#7																
Customer's gaze direction method	27/01/2022	5	1	1	1	0	1	1	0	0	0	0	0	0	0	0
Identify customer interest	05/02/2022	5	0	0	0	0	0	0	0	1	1	1	1	1	0	0
User story #8,#9																
Testing data	10/02/2022	5	1	1	1	1	1	0	0	0	0	0	0	0	0	0
Output generation	20/02/2022	5	0	0	0	0	0	0	2	2	2	0	0	0	0	0
Total		40	4	4	3	3	4	3	3	5	4	2	2	2	1	0

Figure 3.4: sprint backlog plan

3.9 SPRINT ACTUAL

Actual sprint backlog is what adequate sprint planning is actually done by project team there may or may not be difference in planned sprint backlog.

Backlog item	Status and completion date	Original estimate in hours	Day1	Day2	Day3	Day4	Day5	Day6	Day7	Day8	Day9	Day10	Day11	Day12	Day13	Day14
User story#1,#2,#3			hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs	hrs
Table design	28/12/2021	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Form design	31/12/2021	3	0	0	2	1	0	0	0	0	0	0	0	0	0	0
Basic coding	08/01/2022	5	0	0	0	0	0	1	1	1	2	0	0	0	0	0
User story #4,#5																
Data set creation	22/01/2022	8	2	0	0	2	0	2	0	0	1	0	1	0	0	0
Detection of face	22/1/2022	5	1	0	0	0	2	0	0	1	0	0	1	0	0	0
User story #6,#7																
Customer's gaze direction method	05/02/2022	5	1	0	0	0	2	0	0	0	0	2	0	0	0	0
Identify customer interest	17/02/2022	7	2	0	0	0	0	2	0	0	0	0	2	1	0	0
User story #8,#9																
Testing data	20/02/2022	5	2	0	0	0	0	0	0	2	0	0	0	0	1	0
Output generation	20/02/2022	4	0	0	0	0	0	0	2	2	0	0	0	0	0	0
Total		44	9	1	2	3	4	5	3	6	3	2	4	1	1	0

Figure 3.5: sprintactual

Chapter 4

Results and Discussions

4.1 Datasets

A. **ICI Dataset**

In order to identify customer interest, it is necessary to analyze customer behaviors in a real-life shopping situation. In a real-life store, there is a shopping situation as well as general situations like walking, looking around something, and talking to each other. However, to effectively analyze customer behaviors while shopping, we need situations that represent customer and product. For this, we collected surveillance videos that contain various customer behaviors, such as stopping in front of a product and gazing at a product. The videos are obtained via YouTube, where we use different languages during the search to maximize the variety and amount of videos. Specifically, a total of 72 videos is collected, where the mean length is 9.7s. The videos contain a fixed frame rate of 20 frames per second and a resolution of 720 x 480, respectively. The dataset consists of the videos captured by real-world CCTV surveillance cameras, with various angles, different lighting conditions, and different resolution quality.

B.**FER Dataset**

One of the ways humans communicate is by using facial expressions. Research on technology development in artificial intelligence uses deep learning methods in human and computer interactions as an effective system application process. One example, if someone does show and tries to recognize facial expressions when communicating. The prediction of the expression or emotion of some people who see it sometimes does not understand. In psychology, the detection of emotions or facial expressions requires analysis and assessment of decisions in predicting a person's emotions or group of people in communicating. This research proposes the design of a system that can predict and recognize the classification of facial emotions based on feature extraction using the Convolution Neural Network (CNN) algorithm in real-time with the OpenCV library, namely: TensorFlow and Keras. The research design implemented in the Raspberry Pi consists of three main processes, namely: face detection, facial feature extraction, and facial emotion classification. The prediction results of facial expressions in research with the Convolutional Neural Network (CNN) method using Facial Emotion Recognition were 65.97 percent.

4.2 Results

Demonstrate the customer's interest classification accuracy.Applying face detection methods, which are essential for estimation of gaze direction, to the ICI dataset and measuring the accuracy of them. The accuracy results of the face detection algorithm in various cases. Here, Case 1 represents when the only front side of the customer's face is detected. Case 2 shows the accuracy result when front and right and left sides of the face are detected. Case 3 is when face direction swings into all sides. The result of the algorithms demonstrates that MTCNN is heavily influenced by the resolution of the video. Considering that real-life shopping surveillance videos are of low quality, with MTCNN, the accuracy of gaze direction suffers significantly. RetinaFace outperforms MTCNN in all cases. However, the pre-trained model used in RetinaFace contains only faces from -99 degrees to 99 degrees, meaning that faces for other angles are not recognized. OpenPose does not use the pre-trained models. However, it outperforms MTCNN and RetinaFace and outputs 71.3 percent. OpenPose demonstrates superior performance compared with MTCNN and RetinaFace because it can detect face direction in all sides even when looking backward or faces that are hard to recognize. demonstrates the results of face detection and estimation of gaze direction using various methods.The results in the situation when the right and left sides of the face are detected.The results when the backsides of the face are detected. In the situation , MTCNN and RetinaFace except OpenPose cannot detect the backside of the face

Chapter 5

Conclusions

This project proposes a method to identify customer's interests in the product through the estimation of gaze direction. For effective identification, the ICI dataset with various quality and conditions, including various behaviors of customers in the real-world store, was proposed. Considering that the accuracy of gaze direction depends on face detection, I applied the state-of-the-art face detection algorithms to the ICI dataset. The experimental results demonstrate that OpenPose based face detection model outperforms MTCNN and RetinaFace and outputs 71.3 percent. In this project,made the following implication. One of the main challenges in estimating gaze direction for identifying customer's interest is when a customer is looking backward. Currently, existing methods are not efficient in detecting the face when a customer is looking backward. Thus, in the future, planning to propose a method to solve this problem based on OpenPose. In addition, the proposed method uses only the human skeleton meaning that it will not affect customer's privacy issues

References

[1] **Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheikh** ,”OpenPose:Realtime multi-person 2D pose estimation using part affinity fields,” in arXiv preprint arXiv:1812.08008, 2018.

[2] **K. Zhang, Z. Zhang, Z. Li, and Y. Qiao** ”Joint face detection and alignment using multitask cascaded convolutional networks,” in IEEE Signal Processing Letters, 23(10):1499–1503, 2016.

[3] **J. Deng, J. Guo, Y. Zhou, J. Yu, I. Kotsia, and S. Zafeiriou** ”Retinaface: Single-stage dense face localisation in the wild,” in arXiv preprintarXiv:1905.00641, 2019.

[4] **T.-Y. Yang, Y.-T. Chen, Y.-Y. Lin, and Y.-Y. Chuang** ”Fsa-net: Learning fine-grained structure aggregation for head pose estimation from a singleimage,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1087-1096, 2019.

Appendix

Source Code

```
import keras
import cv2
from keras.models import model_from_json
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator

import numpy as np
from src.dbconnection import *
model = model_from_json(open(r"model/facial_expression_model_structure.json", "r").read())
model.load_weights(r'model/facial_expression_model_weights.h5') # load weights



face_cascade = cv2.CascadeClassifier(r'model/haarcascade_frontalface_default.xml')

cap = cv2.VideoCapture(0)


emotions = ('angry', 'disgust', 'fear', 'happy', 'sad', 'surprise', 'neutral')

def camclick():
   i=0
   while(True):
      ret, img = cap.read()

      # img = cv2.imread('../11.jpg')
      # cv2.imwrite(str(i)+".jpg",img)
      i=i+1

      gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

      faces = face_cascade.detectMultiScale(gray, 1.3, 5)

      #print(faces) #locations of detected faces
      emotion=None

      emotionlist=[]

      for (x,y,w,h) in faces:
         cv2.rectangle(img,(x,y),(x+w,y+h),(255,0,0),2) #draw rectangle to main image

         detected_face = img[int(y):int(y+h), int(x):int(x+w)] #crop detected face
         detected_face = cv2.cvtColor(detected_face, cv2.COLOR_BGR2GRAY) #transform to gray scale
         detected_face = cv2.resize(detected_face, (48, 48)) #resize to 48x48
```

```
            img_pixels = image.img_to_array(detected_face)
            img_pixels = np.expand_dims(img_pixels, axis = 0)

            img_pixels /= 255 #pixels are in scale of [0, 255]. normalize all pixels in scale of [0, 1]

            predictions = model.predict(img_pixels) #store probabilities of 7 expressions

            #find max indexed array 0: angry, 1:disgust, 2:fear, 3:happy, 4:sad, 5:surprise, 6:neutral
            max_index = np.argmax(predictions[0])

            emotion = emotions[max_index]
            cv2.putText(img,emotion,(x,y-5),cv2.FONT_HERSHEY_SIMPLEX,0.5,(255,0,0),2)

            emotionlist.append(emotion)

            # if cv2.waitKey(1):
        cv2.imshow('img', img)

        if cv2.waitKey(1) & 0xFF == ord('q'): # press q to quit
            break
        # 'angry', 'disgust', 'fear', 'happy', 'sad', 'surprise', 'neutral'
        if 'angry' in emotionlist or 'disgust' in emotionlist or 'sad' in emotionlist or 'fear' in emotionlist or 'happy' in
              emotionlist:
            import datetime
            fn=datetime.datetime.now().strftime("%Y%m%d%H%M%S")+".jpg"
            cv2.imwrite("static/noti/"+fn,img)
            qry="INSERT INTO `camnoti` VALUES(NULL,1,%s,NOW(),'pending')"
            val=(fn)
            iud(qry,val)
        # kill open cv things
    cap.release()
    cv2.destroyAllWindows()
            #  pass
        # return emotion
            #write emotion text above rectangle

camclick()
```

Database Design

Attribute Name	Datatype	length	Description
id	Integer	11	Not Null,Auto Increment
username	Varchar	20	Not Null
password	Varchar	20	Not Null
type	Varchar	20	Not Null

Table A.1: login

Attribute Name	Datatype	length	Description
id	Integer	11	primary key,Not Null,Auto Increment
lid	Integer	11	Not Null
fname	Varchar	20	Not Null
lname	Varchar	20	Not Null
gender	Varchar	20	Not Null
place	Varchar	20	Not Null
place	Varchar	20	Not Null
post	Varchar	20	Not Null
pin	bigint	20	Not Null
dob	date	20	Not Null
phone	bigint	30	Not Null
email	Varchar	20	Not Null

Table A.2: staff

Attribute Name	Datatype	length	Description
id	Integer	11	primary key,Not Null,Auto Increment
cameranumber	Varchar	20	Not Null

Table A.3: camera

Attribute Name	Datatype	length	Description
id	Integer	11	primary key,Not Null,Auto Increment
notification	Varchar	40	Not Null
date	date		Not Null
camid	integer	11	Not Null

Table A.4: notification

Attribute Name	Datatype	length	Description
id	Integer	11	primary key,Not Null,Auto Increment
work	Varchar	30	Not Null
staff$_id$	Integer	11	Not Null
date	date		Not Null
status	Varchar	30	Not Null

Table A.5: work

Attribute Name	Datatype	length	Description
id	Integer	11	primary key,Not Null,Auto Increment
camid	integer	11	Not Null
notification	varchar	30	Not Null
datetime	varchar	30	Not Null
status	Varchar	30	Not Null

Table A.6: camnotification

DaTaflow Diagram

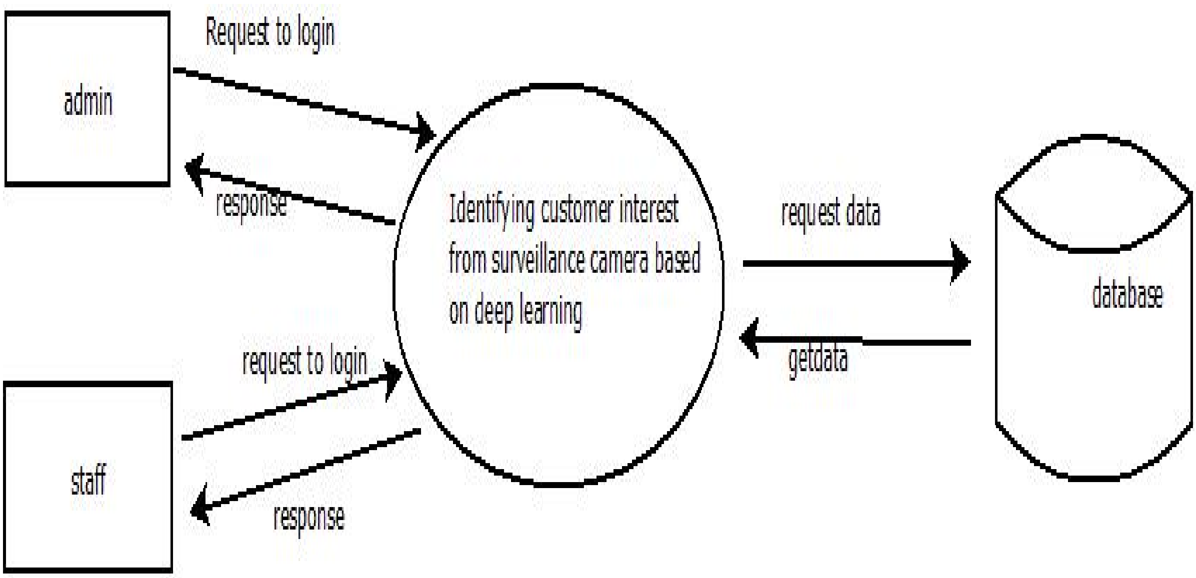

Figure A.1: level0

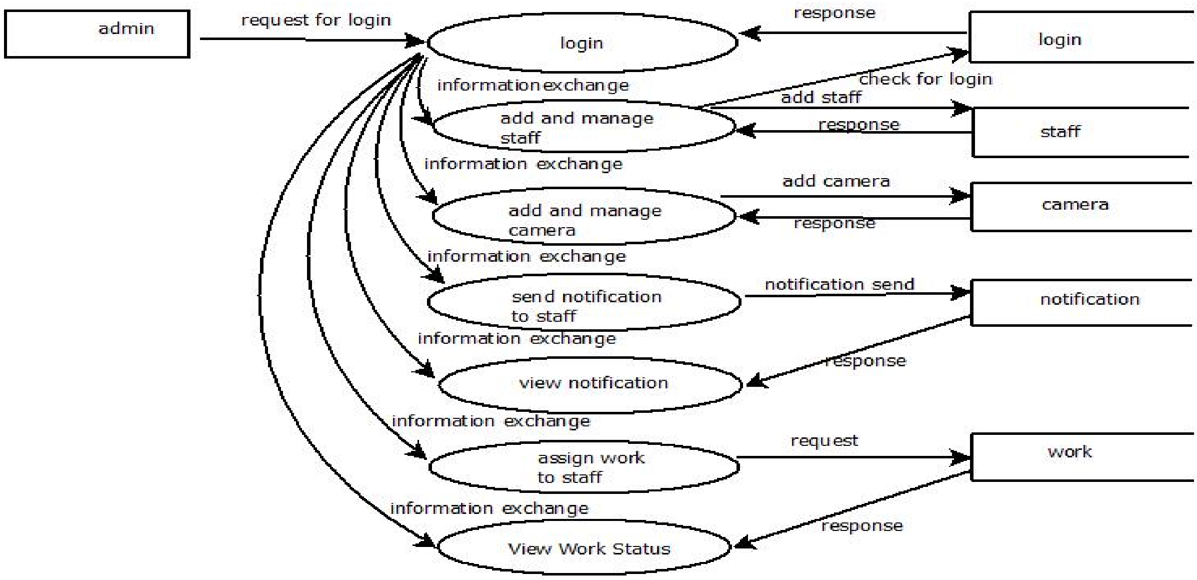

Figure A.2: level1.1

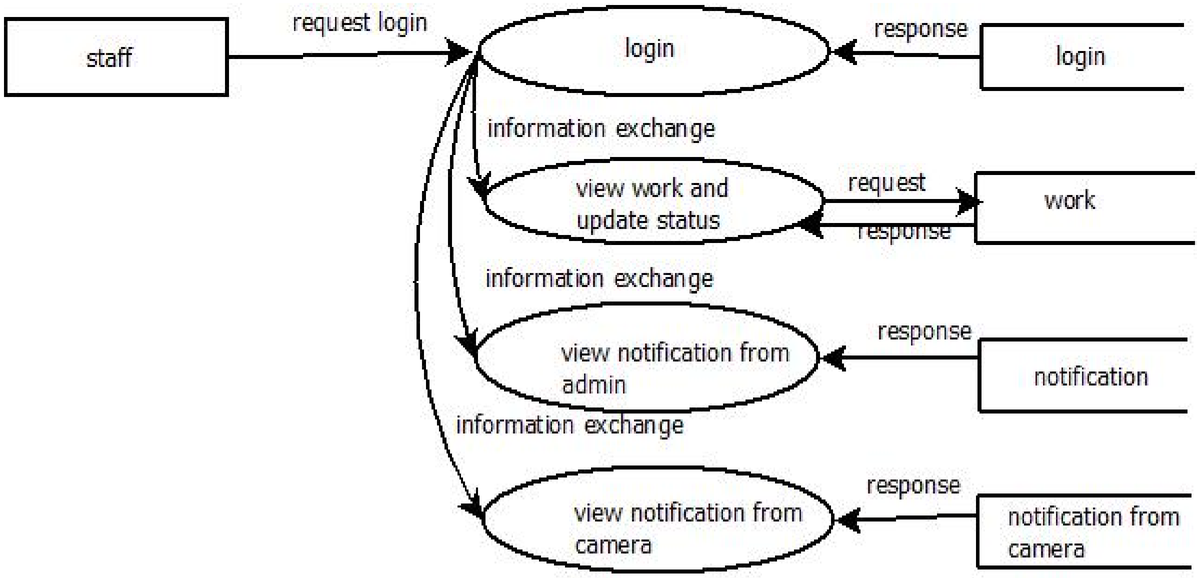

Figure A.3: level1.2

5.1 User Interface

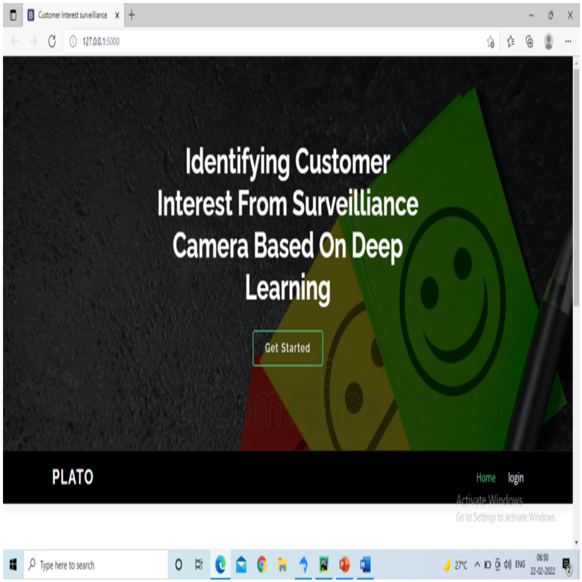

Figure A.4: web1

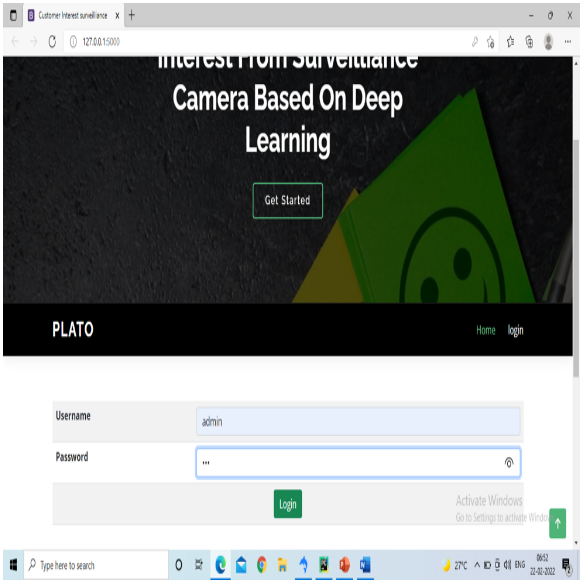

Figure A.5: web2

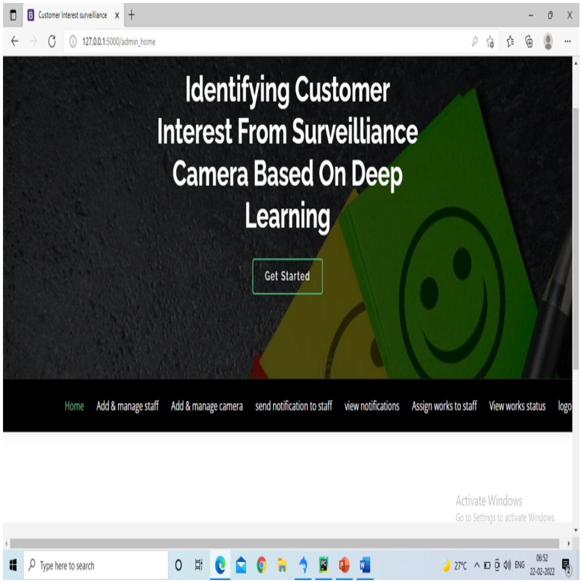

Figure A.6: web3

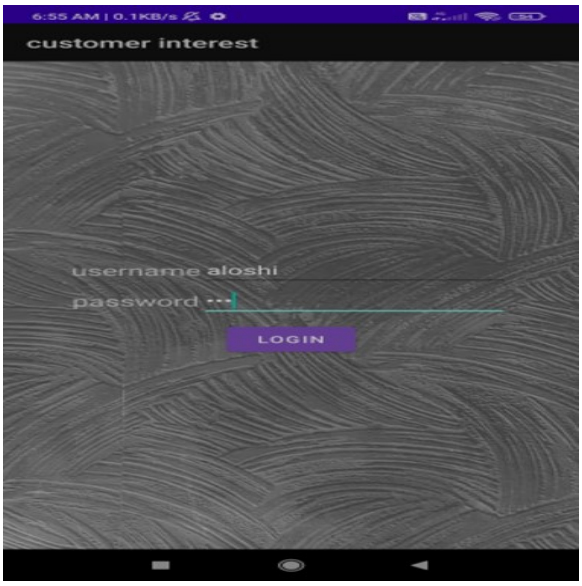

Figure A.7: web4

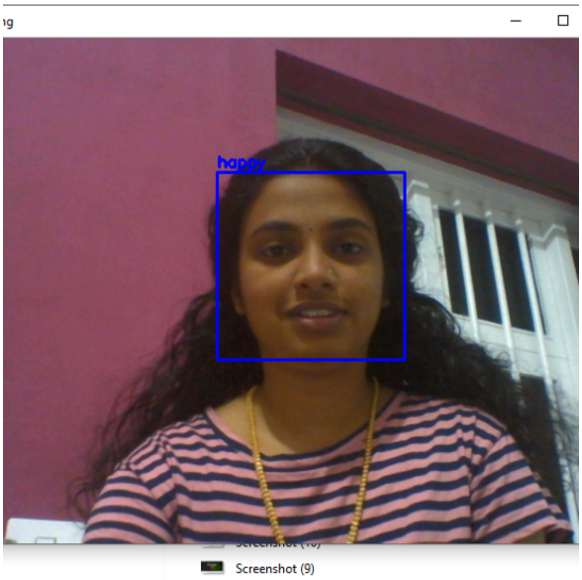

Figure A.8: web5